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Parantap Basu and Sigit S. Wibowo

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Centre for Economic Growth and Policy
Durham University Business School
Mill Hill Lane
Durham DH1 3LB, UK
Tel: +44 (0)191 3345200
www.durham.ac.uk/business/cegap

An Empirical Investigation of Risk Sharing among Indonesian Households

Parantap Basu[1]

and

Sigit S. Wibowo[2]

parantap.basu@durham.ac.uk

sigit.sw@ui.ac.id

Dept. of Economics and Finance, Durham University Business School, Durham University, UK

and

Faculty of Economics and Business, Universitas Indonesia, Depok, Indonesia 16424

ABSTRACT

This study investigates the barriers to risk-sharing among Indonesian households. We test alternative risk sharing models, namely full risk sharing, borrowing-saving, saving only, hidden income, moral hazard and limited commitment among households. Based on three waves of the Indonesia Family Life Survey (IFLS) dataset, we find that the full risk-sharing hypothesis fails. A nested regression framework suggested by Kinnan (2014) provides evidence in favor of the hidden income hypothesis. However, such a nested framework is unable to discriminate between moral hazard and limited commitment. This motivates us to resort to a non-nested framework. Within this non-nested framework, we test two risk sharing models: (i) the Kocherlakota-Pistaferri (2010) moral hazard model with full commitment and (ii) the Ligon et al. (2002) dynamic limited commitment model. IFLS data reject (i) but there is weak evidence of (ii). Based on this, we conclude that there are two hidden barriers to risk sharing among the IFLS households, namely hidden income and limited commitment.

Subject headings: Keywords: credit access, risk sharing, limited commitment

1. Introduction

Households in developing countries are vulnerable to income risks which could emanate from various sources such as crop failure, job-loss, illness, accident to name a few. In the presence of full insurance, these idiosyncratic risks can be pooled by the insurance markets and an individual's consumption is freed from dependence on his own income. However, the absence of perfect insurance arrangement is pervasive in many emerging countries as they do not have a well-developed financial system. Due to the absence of proper insurance markets, households in these economies make informal risk sharing arrangements. There is a growing literature documenting this kind of risk sharing arrangement (Platteau (1991), Udry (1994), De Weerdt and Dercon (2006), Collins *et al.* (2010), Fafchamps and Ferrara (2012), among others).

In this paper, we investigate the mode of risk sharing among the Indonesian households. As one of the emerging economies, Indonesia has been struggling in developing its financial systems. Majority of the population still have difficulty in accessing financial services. Households, particularly those who are working in the informal sectors and in rural areas, have little or no access to insurance and are often not aware of any basic social security provided by the government. These people are vulnerable not only to idiosyncratic or individual risks, but also to aggregate risks. For example, Thomas and Frakenberg (2007) show that the financial crisis in 1997 has affected households in Indonesia across the board. They also found that there was a significant increase in the incidence of poverty and a decline in living standards as the crisis unfolded. The effects were indicated by lower levels of consumption and income, decrease in households' assets and a reduction in human capital investment.

Our study is inspired by Kinnan (2014) who performs a similar exercise using panel data for Thai households. While Kinnan uses Thai panel household data to test alternative risk sharing models, we use a large panel of Indonesia Family Life Survey (IFLS) dataset to test alternative risk sharing models. Kinnan conducts all the empirical tests based on an econometric specification that nests alternative risk sharing models. We go beyond Kinnan's *nested framework* and test new risk sharing models which cannot be adequately nested. The IFLS micro dataset is quite rich and detailed to enable us to undertake these tests using relatively recent models of risk sharing in the presence of private information and limited commitment.

Using three waves of a panel data of 10,435 IFLS households, we first undertake a test of a standard full risk sharing among households which requires that each household's consumption should not depend on its own income if the risk sharing is perfect. After adequately controlling for community waves and household fixed effects, we find that the full risk sharing hypothesis is overwhelmingly rejected by the IFLS data. In the next step, we test five extant models of risk sharing using a nested framework suggested by Kinnan (2014). These five models are namely, (i) borrowing-saving (PIH), (ii) liquidity constraint or saving only, (iii) moral hazard, (iv) limited commitment and (v) hidden income. Our IFLS data reject borrowing-saving and saving only models and lend support to hidden income hypothesis.

Kinnan's nested framework cannot distinguish between moral hazard and limited commitment scenarios. Thus even though one rejects both, one does not know which environment is rejected, that is, moral hazard or limited commitment or both. To get a better understanding of the risk sharing mechanism, we, therefore, resort to non-nested frameworks. We dissociate moral hazard from limited commitment by picking the model of Kocherlakota and Pistaferri (2009) which provides a testable hypothesis when there is private information about efforts and types of agents but the risk sharing contract is subject to full commitment. We call this the *moral hazard only* model. Our test with the IFLS waves reject this model.

Given that *moral hazard only* model is rejected by the IFLS data, the next test candidate is limited commitment hypothesis. With limited commitment, households stay in an informal risk sharing network which thrives on an arrangement of "quasi credits" designed for mutual insurance as described in several studies such as Lund and Fafchamps (1997) and Udry (1994). In most cases of such informal risk sharing networks, there are no legal record or procedure to enforce repayment. The system is thus vulnerable to reneging. For a sustainable informal risk sharing community network, it is important that the long term benefit of helping each other in the risk sharing network must exceed the short term cost of making a sacrifice. We pick a model of dynamic limited commitment à la Ligon et al. (2002). In such a model, in order to stay in a network with limited commitment, each household follows a simple updating rule for the ratio of its own marginal utility consumption to the marginal utility of consumption of the rest of households in the community. This makes this marginal utility ratio *history dependent*. Since there is no moral hazard element in this model, we call it a *limited commitment only* model. We find some weak evidence in favour of limited commitment among the IFLS households.

2. Related Literature

Some early papers on risk sharing tests assumed complete market hypothesis to explain consumption insurance across households. Moreover, the risk sharing hypothesis at the household level is calibrated and tested using very rich data sources such as US Panel Study Income Dynamics (Cochrane, 1991) and US Consumer Expenditure Survey (Mace, 1991). However, empirical investigations of full risk sharing using micro data tend to reject the efficient risk sharing hypothesis. Using consumption, labor supply and wage data in the United States, Attanasio and Davis (1996) conclude that consumption risk sharing is incomplete.

There is a growing literature on the study of risk sharing arrangement in developing countries. Beck *et al.* (2008) show that many households in low-income countries do not have adequate access to the financial services which are taken for granted by households in developed countries. They found that these barriers have strong linkages with economic development and financial accession measures. Therefore, households need to find an efficient way to smooth their consumption and to insure themselves against idiosyncratic shocks.

Other related studies investigate risk sharing arrangements formed by households within the same unit, such as a village or a community. Within a community, the mechanism may take place between families and friends who facilitate risk sharing between economic agents, for instance between young and old, and between families in specific regions. Simply, this can happen because there is mutual assistance among them. This becomes important particularly for low-income and developing economies where access to finance is absent or limited and risk becomes ubiquitous. The insurance mechanism is usually conducted via state-contingent transfers such as in Townsend (1994) and Udry (1994).

However, such informal risk sharing arrangement is fragile due to the immutable limited commitment of group members. The transfers between households in an implicit contract may not occur perfectly if an individual does not comply with the group's terms and conditions. Another possible reason is that usually there is no collateral when risk sharing groups emerge. Ligon, Thomas and Worrall (2002) develop a dynamic contract theoretic model to derive the efficient consumption allocations in village economies and test the model using Indian villages. We use their framework to test the risk sharing subject to limited commitment among the IFLS households.

In the Indonesian context, Ravallion and Dearden (1988) study risk sharing in terms of private transfers between Javanese households in Indonesia using 1981 Susenas data. They find a difference between rural and urban households in terms of transfer behavior. Okten and Osili (2004) utilize IFLS1 and IFLS2 datasets to investigate how consumption smoothing may occur from accessing the credit market. They find that social and community networks are important in gaining access to credit markets. Witoelar (2013) studies how risk sharing emerges within families using IFLS dataset. However, there is hardly any study that investigates the barriers to insurance and alternative forms of risk sharing specifically among Indonesian households.

3. A Survey of Key Models of Risk Sharing

In this section, we provide a brief survey of a few core models of risk sharing which are taken to the data. The main thrust of this brief survey is to understand the structure of the reduced form consumption-income relationships of households. This survey highlights that different risk sharing arrangements imply different testable reduced form consumption processes.

3.1. Full Risk Sharing

The perfect risk sharing model is based on the assumption of complete markets as in Arrow and Debreu (1954) and Arrow (1964), widely known as the Arrow-Debreu model. Under full insurance, each household's consumption does not move in unison with its own income because households can use the asset markets to pool individual income risks. To test this, we can use Townsend's (1994) standard test of full risk sharing using all waves of data. The key risk sharing equation is given by:

$$\ln c_{i,t} = \alpha \ln y_{i,t} + \theta_i + \gamma_j + \delta_t + \varepsilon_{it} \tag{1}$$

where $c_{i,t}$ denotes household i's consumption at date t, $y_{i,t}$ denotes household i's income at date t , θ_i stands for household fixed effect, γ_j denotes village or community fixed effect, δ_t denotes wave effect, and ε_{it} denotes irregular noise. The key null hypothesis is $\alpha = 0$. If the term α is significant, it implies that household i's income tracks its consumption. This means rejection of full risk sharing hypothesis.

3.2. Limited Risk Sharing

If full risk sharing breaks down, several possibilities of limited risk sharing lend themselves. Households may operate in an incomplete market environment with an access to borrowing and lending at a risk-free rate. We call these models as *borrowing-saving* or *permanent income hypothesis* (PIH) models because these models are mostly designed to smooth consumption over time in the spirit of traditional permanent income hypothesis.[1] Hall (1978) shows that in such an environment marginal utility follows a random walk. Alternatively, households may only be able to save but not to borrow (liquidity constrained). This means that the standard Euler equation is not applicable because of liquidity constraints. Following Deaton (1991), this leads to a *saving-only* model where the lagged income may contain information that cannot be captured by consumption in the same period. The current consumption could be then higher than the last period's consumption when the household experiences a low last period income. The underlying rationale is that if income is a mean reverting process, a low income shock last period may indicate that a liquidity constrained household who cut back last period consumption would increase today's consumption to smooth consumption over time.

[1]Of course the notion of consumption smoothing can be broadened to include full risk sharing models where the consumption smoothing happens across states.

In a moral hazard model, work effort in the production process is private information to the household. Introducing incentive constraints on the household to elicit effort invalidates full insurance and gives rise to an inverse Euler equation first derived by Rogerson (1985) as follows:

$$\beta R E_{t-1} u'(c_{it})^{-1} = u'(c_{it-1})^{-1} \tag{2}$$

where β denotes the subjective discount factor, R denotes interest rate and $u'(c_{it})$ is the marginal utility of consumption of the i-th household at date t, E_{t-1} is the expectation at date $t-1$. Kinnan (2014) uses the methodology of Fernandes and Phelan (2000) and show that such a lagged inverse Euler equation representation is robust when the distribution of income depends on past and the current effort. Besides the shadow price of the resources of the community, the household's inverse marginal utility is independent of all information at date $t-1$. Thus adding household's income on the right hand side of (2) will not provide any additional explanatory power.

When effort is contractible but the community does not observe household's income, it gives rise to another form of barrier to insurance known as *hidden income*. Thomas and Worrall (1990) derive optimal contracting arrangement under which the household finds it incentive compatible not to hide its income. Using this lead, Kinnan (2014) shows that under hidden income, the inverse Euler equation formulation (2) is modified by inclusion of the lagged income (y_{it-1}) with a non-negative coefficient as an additional explanatory variable.

Another friction could emerge if the household could potentially walk away from an insurance network at any time by going to autarky. This form of barrier to risk sharing is known as *limited commitment*. To prevent such defection, a planner has to impose a participation constraint on the household. Kinnan (2014) shows that such a constraint again gives rise to an inverse Euler equation structurally similar to (2). This gives rise to a difficulty in disentangling a limited commitment model from a standard moral hazard inverse Euler equation.

3.2.1. A Nested Formulation of Limited Risk Sharing Models

Following Kinnan (2014), we resort to a nested formulation of five models of limited risk sharing namely, (i) borrowing-saving (PIH), (ii) liquidity constraint or saving only, (iii) limited commitment, (iv) moral hazard, and (v) hidden income. (i) and (ii) involve a standard Euler equation while (iii), (iv) and (v) involve an inverse Euler equation as in (2) which implies a nonlinear relationship current consumption (c_{it}), lagged consumption (c_{it-1}), lagged income (y_{it-1}) and shadow price of village resources (η_t). With a log utility specification, Kinnan derives the following loglinear specification:

$$c_{it} = \alpha c_{it-1} + \beta c_{it-1}\eta_t + \theta\eta_t + \gamma y_{it-1} \tag{3}$$

where η_t is the village-wave fixed effect measured by $\sum_{j\neq i} \frac{c_j}{N_v-1}$ with N_v being the size of the village v. All three models of limited risk sharing, namely (iii), (iv) and (v) suggest the presence of the multiplicative term $c_{it-1}\eta_t$. If $\beta = \gamma = 0$, it reduces to PIH models (i). If $\beta = 0$ but $\gamma < 0$, then the data lend support for saving only model. If $\beta \neq 0$, $\theta \neq 0$, but $\gamma > 0$ then data support to hidden income hypothesis (v). On the other hand, if β and θ are nonzero but $\gamma = 0$, one cannot distinguish between moral hazard and limited commitment models.

3.3. Non-nested models of limited risk sharing

Since Kinnan's nested framework is unable to distinguish between moral hazard and limited commitment, one needs to study moral hazard and limited commitment models separately. We now consider two non-nested models, one focusing on moral hazard and the other concentrating on limited commitment.

3.3.1. Kocherlakota-Pistaferri (2009) moral hazard model

Kocherlakota and Pistaferri (KP hereafter) model an environment where households join a community and agree to exert effort to produce output for the community. An example is the case of households forming an informal group to cultivate crop for the community. Household's income is not private information but its effort and productivity are. In such a scenario, the household has an incentive to shirk (moral hazard) or misrepresent its type (adverse selection). KP derive the efficient contracting arrangement of this scenario by setting up a constrained social planning problem where the social planner offers a contract of consumption and work effort to the participating households in a community which maximizes their expected utility subject to two constraints, namely (i) a participation constraint ensuring not to walk away to an autarky, and (ii) a truth telling constraint which means that the household has no incentive to shirk or misrepresent its type. The first order condition gives rise to again an inverse Euler equation as in (2). Invoking the law of large numbers, Kocherlakota and Pistaferri derive the following stochastic discount factor ($sdf_{t-1,t}$) based on cross sectional raw moments of consumption of the households in the community between dates $t-1$ and t which they call Private Information Pareto Optimal (PIPO) sdf:

$$sdf_{t-1,t} = \frac{C_{t-1}^{\gamma}}{C_t^{\gamma}} \tag{4}$$

where C_{t-1}^{γ} is the γ^{th} cross sectional raw moment in the community at date $t-1$ and γ is the relative risk aversion parameter. Due to the application of law of large numbers, this *sdf* is robust to the stochastic process generating household's hidden skills and thus it does not depend on household's longitudinal history of characteristics. In addition, it is robust to possible mismeasurement of consumption.

The moral hazard environment of KP model is fundamentally different from Kinnan's formulation. In KP's moral hazard model, a social planner solves a constrained allocation problem where it is incentive compatible for the households to reveal its type and effort and participate in such a contract market that opens only once at the start of time. This contract is, therefore, a *full commitment contract* which means that the household after signing such a contract cannot renege or re-contract. In Kinnan's formulation we cannot distinguish between moral hazard and limited commitment. In the KP model, there is no issue of limited commitment because agents have full commitment to start with. Thus we call KP a model of *moral hazard only.*[2]

The PIPO sdf can be applied to a wide class of incomplete market environments.[3] Applying this to a simple credit market environment as in the preceding consumption smoothing model where households have access to borrowing and lending at a gross risk free rate R, the standard Euler equation can be written as:

$$E_{t-1}\frac{RC^{\gamma}_{t-1}}{C^{\gamma}_{t}} = 1 \tag{5}$$

which E_{t-1} is the expectation operator at date $t-1$. Taking the log-transform and assuming homoskedastic errors, we can rewrite (5) as a regression equation as log-linear random walk process for the γ^{th} cross-sectional raw moment of consumption,

$$\ln C^{\gamma}_{t} = a + \ln C^{\gamma}_{t-1} + \varepsilon_t \tag{6}$$

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[2]Strictly speaking, KP model also incorporates adverse selection. At any date, agent's effort and type are both private information. We abstract from these details and label KP as a moral hazard model without any issue of commitment.

[3]Basu *et al.* (2011) apply this PIPO discount factor to test international risk sharings.

where a denotes a constant and ε_t denotes the residual error. Motivated by this random walk specification of the cross sectional raw moments, we propose the following regression to test Kocherlakota and Pistaferri's risk sharing model of private information (2009) for each community:

$$\ln\left(\frac{\sum_{i=1}^{N_k} c_{ik,t}^{\gamma}}{N_k}\right) = \alpha_0 + \alpha_1 \ln\left(\frac{\sum_{i=1}^{N_k} c_{ik,t-1}^{\gamma}}{N_k}\right) + \alpha_2 \ln y_{k,t-1} + \theta_k + \varepsilon_{k,t} \tag{7}$$

where $c_{ik,t}$ is household i's consumption in community k at date t, $y_{k,t}$ denotes average income at community k at date t, θ_k denotes the community-fixed effect, and $\varepsilon_{k,t}$ denotes error terms. N_k is different from community to community. If this risk sharing environment is true, α_1 should be close to unity and no other variables such as past income of the community should have any additional explanatory power in determining the left hand side cross sectional raw moment which means that α_2 should equal zero for a plausible range of risk aversion parameter, γ.

3.3.2. Dynamic Limited Commitment Model of Ligon et al. (2002)

The contract stipulated by KP is not time consistent due to full commitment assumption. Agents can sign such a contract at date zero but renege on it at a later date due to limited commitment. Thus limited commitment needs to be modelled separately in a non-nested framework. In the Ligon et al. (2002) model of limited commitment, households form an informal risk sharing group with a "quasi credit" arrangement. There are no written records, legal provisions, or collateral to enforce repayment. There is an implicit understanding that there may be delay in repayment or forgiving of the debt in extenuating circumstances. Agents still form such informal risk sharing arrangement because the perceived long term benefits of adhering to such group may outweigh the short term costs. Assuming a finite state Markov process for income, Ligon et al. consider first a bilateral risk sharing arrangement where it is not incentive compatible for any of the households to break away from such a contract and go to autarky. In this model, agents are only subject to a participation constraint and there is no issue of private information about effort and type. This makes the Ligon et al. (2002) model a *limited commitment only* model without any issue of moral hazard. The optimal contracting arrangement in Ligon et al. gives rise to a simple updating rule for the marginal utility ratio of any two participating households in such a bilateral contract. The marginal utility ratio becomes history dependent if any of the household members is constrained in the sense that she receives the minimum surplus from staying in the network. The minimum surplus is defined as the surplus which keeps her indifferent between staying in the network or going to autarky.

The bilateral risk sharing arrangement is not realistic in the context of IFLS households because typically risk sharing group involves more than two households in a village. We, therefore, use a variant of the estimation equation suggested by Ligon et al. (2002) in the context of a power utility. We consider the efficient contract between a typical household (i) in each village with the rest of households in the same village. In other words, we run the following regression:

$$\frac{c_{it}}{\bar{c}_{-i,t}} = \alpha_0 + \alpha_1 \frac{c_{it-1}}{\bar{c}_{-i,t-1}} + \alpha_2(\text{village characteristics}) \ + \xi_{it} \tag{8}$$

where $\bar{c}_{-i,t}$ denotes the average consumption of all households in the same village except the i^{th} household and ξ_{it} denotes random disturbance term. These village characteristics could be of several kinds, namely existence of formal risk sharing arrangement, proximity to formal financial institutions, relative preponderance of urban to rural households. After controlling for these effects, if α_1 is found to be statistically significant, it means history dependence of the consumption share of a participating household in the community. This can be viewed as an evidence of dynamic limited commitment in the risk sharing arrangement.[4]

[4]Note that a lack of history dependence does not necessarily mean an absence of limited

Table 1 summarizes all the risk sharing arrangements reviewed in this section.

(INSERT TABLE 1 HERE)

4. Data

All our data are gathered from the Indonesia Family Life Survey (IFLS). These longitudinal surveys consist of two levels: community and household surveys where the latter can be decomposed into individual and family levels. There are four waves available: IFLS1 in 1993, IFLS2 in 1997, IFLS3 in 2000, and IFLS4 in 2007. In IFLS, around 90% of sample households are retained from the first wave until the latest which is considered to be the advantage of using this dataset to make an economic analysis of risk sharing and related testable implications. For this study, we only use IFLS data up until Wave 3.[5]

For the empirical analysis, we make sure that the data fulfill some basic conditions: (i) all necessary information regarding household variables are available, meaning that only households that exist for all waves are considered, (ii) relevant variables, particularly

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commitment risk sharing. The history dependence arises when one of the participants in the risk sharing network is constrained in the sense that he/she is held down to the minimum surplus to keep this risk sharing arrangement viable. In the absence of such corner solution, the consumption ratio remains time invariant which replicates a first best risk sharing scenario within a limited commitment framework. We abstract from this complication by assuming that at least one household member in the network is always constrained which makes the consumption ratio history dependent.

[5]We cannot utilize IFLS4 data due to inadequate information about the consumption data making it difficult to compare across waves.

consumption and income, do not take extreme values[6]; and (iii) households stay within their villages for the whole period.

In IFLS1, the number of households is 7,224 while in IFLS3, there are 10,435 households. For testing the Kinnan's (2014) nested regression model, KP (2009) model and Ligon et al. (2002) model, we cannot use the whole sample due to the restriction imposed by the balanced nature of the panel. Many households cannot be observed across two successive waves mostly due to family migration and incomplete household characteristics such as employment and socio-economic status. In most cases, we work with around 3,194 households who live in 310 villages or communities.

The consumption is measured by per capita expenditure (PCE) and the income is also measured by per capita income (PCI). This means that the consumption and income for each household is divided by the number of people living in that household. For the last two waves, around one third of IFLS households have five or more persons living within a household. Households with 2, 3 and 4 persons are relatively similar for waves 2 and 3 surveys. The descriptive statistics for relevant analysis are given in Table 2. Figure 1 plots the averages of community consumption and income as a summary description of the data. The upward sloping nature of the scatter indicates that full risk sharing hypothesis is unlikely to be supported by the data.

(INSERT TABLE 2 AND FIGURE 1 HERE)

To examine private information model with hidden efforts, we use information at community level by summing up all household consumption and income within a

[6]Extreme values are defined as five percentiles from the top and bottom of the distribution.

community which is the same as village in the IFLS data. We then compute raw moments for all communities in IFLS using (7) in order to assess risk sharing model with private information.

To test dynamic limited commitment models as formulated in (8) we use community (or village) as a risk sharing unit. Since in the dynamic limited commitment model our aim is to test for the memory of the contractual arrangement, it is important that we have a balanced panel with the same households observed in two successive waves. This restricts us to waves 2 and 3 with about 2,999 households. We use community data that exist from IFLS1 to IFLS3. This leaves us with 310 communities for this test. Based on IFLS1, the average number of households within a community is 16.5 households. Each household's consumption in a community is divided by the average consumption of all households in the same community based on the regression Equation (8). Since only two waves of data are used, the limited commitment regression thus reduces to a cross-sectional regression.

To assess risk sharing within communities, the IFLS provides information about community participation known as Rotating Saving and Credit Associations (ROSCA for short) for each respondent along with individual social and economic characteristics. ROSCAs (or *Arisan*) have long been known in Indonesia as a part of the social and economic tradition. Indonesian households use various forms of ROSCA to share their risk. With diverse demographic characteristics, ROSCAs are generally formed by group of people who usually congregate weekly and pass part of the pooled assets in certain ways using either a random pot or a systematic rotation scheme. Since ROSCAs use a simpler approach to conducting financial contract than formal financial institutions, a lot of people, especially those who are credit constrained, prefer to use it as a risk sharing vehicle. This makes ROSCAs specifically a good candidate for using it as a village fixed effects for limited commitment regressions. Unfortunately, IFLS1 does not have information about ROSCAs.

This is another reason why we use the data from IFLS3 and IFLS2 to test dynamic limited commitment models.

4.1. Choice of instruments

The empirical specification such as in Equation (1) may suffer from two potential problems. These problems may arise if ordinary least squares (OLS) estimators are applied to estimate equations that include consumption and income, namely the endogeneity of income change and income measurement error. Similar issue arises also for the nested empirical specification (3). To address these potential problems, we use two sets of instrumental variables (IVs) for household and community level tests. For household level, we have asset measures, health measures and rainfall rate. The justification for using the first two variables as instruments is that households with greater physical and human assets are likely to have higher income. The first instrument is household assets which include current and fixed assets. In the IFLS data, these household assets include the house, vehicles, appliances, savings, jewelry, furniture and utensils. We also include assets that are used by households for farming and non-farming businesses.

Our second instrument is activities for daily living (called ADL hereafter). ADL is a measure that indicates the physical ability of an individual to perform daily living activities. The reliability and validity of ADLs have been tested extensively, mainly in the United States and Southeast Asia.[7] The ADL is transformed into an index as follows:

$$\frac{ADL\ Score - Min.\ Score}{Max.\ Score - Min.\ Score}.$$

The ADL index takes on values from 0 to 1, where zero is when the individual cannot

[7] Gertler and Gruber (2002) provide more explanation about the reliability and validity of ADLs in this regard.

perform any ADLs at all and one is when the individual can easily perform all of the ADLs.[8] ADL is deemed to be a good instrument because it is likely to be strongly correlated with income because individuals with greater physical ability are likely to generate more income.

It is conceivable that asset of the household could be correlated with consumption and thus making it a weak instrument. To mitigate this problem we use rainfall as an additional instrument which is likely to be strongly correlated with income. Since most of the regions in Indonesia are dominated by agricultural occupation, rainfall is an effective instrumental variable (see for example Fichera and Savage, 2015). The daily rainfall data are obtained from the Indonesian Agency for Meteorological, Climatological and Geophysics (BMKG). We use the previous year's average precipitation for each IFLS wave respectively, then match these data using community data using altitude and longitude to nearest BMKG weather station. The data from 25 BMKG stations are matched with 310 IFLS communities. The matching process is done by calculating a community location to the nearest station.

[8] In IFLS, the ADLs are divided into several components. These are namely, ability to carry a heavy load for 20 meters, ability to walk for 5 kilometers, ability to walk for 10 kilometers, ability to bow, squat and kneel, ability to sweep the house floor, ability to draw a pail of water from a well, ability to stand up from sitting on the floor without help, ability to stand up from sitting position in a chair without help, ability to bathe without help, and ability to dress without help. The first four activities are classified as intermediate ADLs, while the last five activities are classified as the basic ADLs.

5. Empirical Results

5.1. Full Risk Sharing Tests

We undertake tests given in Equation (1) is employed. The results are presented in Table 3 for five specifications. Column (1) reports OLS results with random effects only which means $\theta_i = \gamma_j = \delta_t = 0$. Column (2) reports the regression after adjusting for heteroskedasticity including household fixed effects but without any village and wave effects which means $\theta_i \neq 0$, and $\gamma_j = \delta_t = 0$. Column (3) reports results with heteroskedasticity adjustment with all three effects included which means $\theta_i \neq 0$, $\gamma_j \neq 0$, and $\delta_t \neq 0$. Column (4) reports the OLS regression with $\theta_i \neq 0$, $\delta_t \neq 0$ and by computing the clustered standard error to allow correlation between IFLS households' unobservable within each village. All these four specifications reject the full risk sharing hypothesis because the estimate of the log of income is significant at the one percent level.

A potential problem with the regressions reported in Columns (1) through (4) is that a classical measurement error and endogeneity could make the regression coefficient of income biased. This bias is the result of the correlation between the right hand side income variable and the error term. To deal with these issues, we instrument these regressions. All our three instruments are used namely, ADL of the household head, log of household's assets, and rainfall rate. The last rainfall instrument is specifically chosen to deal with the issue of exogeneity of income. Column (5) reports the IV-2SLS regression with clustered standard error.[9] Our IVs pass the usual Sargan test of overidentifying restrictions, and the Kleibergen-Paap rk LM statistic of underidentification. The Cragg-Donald Wald F statistic exceeds the Stock-Yogo critical value suggesting that our IVs are not weak. This battery of

[9]Since standard errors are already clustered, we drop the village fixed effects which means $\gamma_j = 0$.

tests basically suggests that our three IVs are adequate. This IV regression clearly rejects the full risk sharing hypothesis because log of income is significant at the 5 percent level. All these five specifications thus overwhelmingly reject the full risk sharing hypothesis.

(INSERT TABLE 3 HERE)

The IV regressions with all its diagnostics basically suggests that our IVs are strong which take adequate care of the classical measurement errors but it does not necessarily address the endogeneity issue. To deal with the issue of endogeneity, we follow the regression based endogeneity test procedure mentioned in Wooldridge (2002, section 6.2.1). We first regress income (y_{it}) on all our three instruments namely, rainfall, ADL, and household asset. In the second step we regress c_{it}, on the fitted y_{it} and the residual from the first step regression. The coefficient of y_{it} in the second step regression is consistent by construction. In Table 4, we report this additional test for endogeneity. Note that the coefficient of y_{it} is 0.25 which is significant at the 1 percent level based on the heteroskedasticity corrected t ratio. This additional two-step regression takes care of the endogeneity issue.

(INSERT TABLE 4 HERE)

5.2. Nested regression

Given that the full risk sharing hypothesis is overwhelmingly rejected by the IFLS data, we next turn to testing limited risk sharing models. Table 5 reports the results of the nested regression (3) for alternative limited risk sharing models. We follow Kinnan (2014) by undertaking an OLS regression adding the village-wave fixed effect via the term η_t. We do not run a conventional fixed effect regression to avoid Nickell (1981) bias due to limited number of waves.

(INSERT TABLE 5 HERE)

The key results of this nested regression are presented in Table 5. Column (1) presents simple OLS regression while Column (2) reports IV regressions with the same three variables included as IVs. Our IVs pass all the diagnostics including the Sargan-Hansen test. Both these regressions suggest that the nonlinear term involving the interaction between the lagged consumption and the village-wave fixed effect is significant. This means that the PIH and saving only model are rejected. The lagged income is found to be positive and statistically significant which suggests evidence of hidden income. In Table 6 we report the same nested regression for agriculture only as a further robustness check and the same conclusion is reached.

(INSERT TABLE 6 HERE)

5.3. Moral hazard only regression

Since Kinnan's nested framework is unable to discriminate between moral hazard and limited commitment, we next report the test results of *moral hazard only* model. Table 7 reports the KP raw moment regression in Equation (7) involving 310 communities for the risk aversion parameter, γ ranging from 1 to 2. To deal with the issue of measurement error and endogeneity, we use the same three instruments but averaged across all households within each village namely, average of household assets in each community, average of ADLs and the rainfall rate in each village from the previous year. Our diagnostics including Hansen, Kleibergen-Paap rk, and Cragg-Donald tests suggest that IVs are adequate for all specifications. For all six specifications, the lagged community average log income is found to statistically significant at the 1 percent level. This suggests that the moral hazard only model is rejected by the IFLS data.

(INSERT TABLE 7 HERE)

5.4. Limited commitment only regression

Turning now to the limited commitment only model of Ligon et al. (2002) based on the regression in Equation (8), we regress the consumption ratio of each household in IFLS3 on the corresponding consumption ratio of IFLS2. Since our regression analysis is focused on these two waves only, it is a cross section regression and therefore, the endogeneity is less of a concern but we still need to worry about measurement error and omitted variable bias. To deal with this, we resort to an IV regression using the same three IVs for each wave. For village characteristics, we choose two controls namely, (i) the presence ROSCA households in a village, and (ii) the preponderance of households with agriculture only occupations. For each of these characteristics, we add an intercept dummy. Instead of village fixed effects, these village characteristics are chosen to avoid the Nickell bias resulting from limited number of waves.

Table 8 provides the estimation results for limited commitment. The first column shows the result of a simple OLS regression taking into account the heterogeneity of households within and across all villages. This is done by a simple heteroskedasticity correction of the standard error. Column (2) reports an IV-2SLS regression with clustered standard errors at the village level to deal with unobserved heterogeneity of households within the same village. Our IVs pass the Sargan test.

Although in our OLS regression, the lagged consumption ratio term is not significant, t ratio is significant at a 10 percent level in the IV regression suggesting weak evidence for limited commitment. We also investigate the possibility of households participating in ROSCA sharing risk more than non-ROSCA households. This is done by interacting the

ROSCA dummy with the lagged consumption ratio. The results are reported in Column (3) of Table 8. Since this interaction dummy is insignificant, we do not find any compelling evidence of greater risk sharing among ROSCA households.

Our regression result suggests that once measurement errors and village level clustering are properly taken into account by the IV regression, there is evidence in favour of the history dependence of the marginal utility ratio along the line suggested by Ligon et al. (2002). This history dependence arises when at least one of the participants in the risk sharing network is constrained in the sense that he/she is held down to the minimum surplus to keep this risk sharing arrangement viable.

(INSERT TABLE 8 HERE)

6. Conclusion

In this paper, we study the barriers to risk sharing among Indonesian households using three waves of IFLS data. Using the extant theoretical literature on risk sharing hypothesis, we test six key risk sharing models. A daunting challenge to testing these risk sharing models using household consumption and income data is the presence of measurement errors and endogeneity which can make the relevant estimates biased. To take care of these issues, we run a battery of tests which include testing overidentifying restrictions, weakness of instruments, and direct test of endogeneity. Our study overwhelmingly rejects full sharing among IFLS households. Using a nested regression framework, we also reject standard borrowing-saving and saving-only models. As in Kinnan (2014), we also find evidence of the hidden income hypothesis. Our IFLS data reject a non-nested *moral hazard only* model à la KP (2009) while there is weak evidence in favour of Ligon et al. (2002) *limited commitment only* model. Thus unlike Kinnan (2014), we cannot rule out limited commitment as another candidate posing a potential barrier to risk sharing among IFLS households.

The rejection of full risk sharing model and alternative models of risk sharing involving imperfect credit markets is not surprising given the pervasive failure of formal credit and insurance markets in these economies. This gives rise to the possibility of informal networks among the Indonesian households. Our study suggests that these networks are fragile because of the immutable human incentive to hide income information as well as not to fully commit to the rules of a village network. A long term solution to remedy all these barriers to risk sharing is to improve household's access to credit market by establishing appropriate financial institutions. Given that such macro policies of financial deepening could take time and resources, piecemeal solutions on a case by case basis could help. The ROSCA network with proper monitoring can be expanded to reach more people in a rural economy. In addition, the government could promote the micro credit agencies to access the villages. More innovative local monitoring and moral suasion of people in a network could straighten commitment among the group members. Banerjee and Duflo (2011) provide several case studies of success stories of this kind of moral suasion in the context of rural India. These steps do not necessarily eliminate the problems of hidden income and limited commitment but could help overcome these barriers to risk sharing.

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Table 1: Summary of Risk Sharing Hypotheses and Related Tests

	Specification	Expected Sign
Full Risk Sharing	Eq (1)	$\alpha = 0$
Nested Models of Risk Sharing, Kinnan (2014)		
PIH	Eq (3)	$\beta = \gamma = 0$
Saving Only	Eq (3)	$\beta = 0$ and $\gamma < 0$
Hidden Income	Eq (3)	$\beta \neq 0$ and $\gamma > 0$
Moral Hazard or Limited Commitment	Eq (3)	$\beta \neq 0$ and $\gamma \geq 0$
Non-nested Models of Risk Sharing		
Moral Hazard Only (KP, 2010)	Eq (7)	$\alpha_2 = 0$
Limited Commitment Only (Ligon et al, 2002)	Eq (8)	$\alpha_1 \neq 0$

Table 2: Summary Statistics of Key Variables

Variable	Obs.	Mean	Std. Dev.	Min	Max
IFLS1 − 1993					
log(Asset)	3,160	16.419	1.8037	9.1528	22.6116
log(PCE)	3,194	11.9568	0.7732	9.3117	15.645
log(PCI)	3,194	10.3974	2.0141	0.9641	18.6922
ADLs	3,194	0.9672	0.0851	0	1
Rainfall rate	3,194	5.3455	1.597	2.789	9.2575
IFLS2 − 1997					
log(Asset)	2,994	17.0124	1.8666	7.6834	23.2693
log(PCE)	3,194	12.3716	0.7755	9.9135	17.2958
log(PCI)	3,194	11.5133	1.4148	-1.5757	18.8558
ADLs	3,194	0.9673	0.0851	0	1
Rainfall rate	3,039	5.3502	1.605	2.789	9.2575
IFLS3 − 2000					
log(Asset)	3,075	16.9376	1.8656	6.2146	22.497
log(PCE)	3,194	12.3821	0.7097	10.2886	15.5103
log(PCI)	3,194	11.5633	1.1696	5.6268	17.2419
ADLs	3,194	0.9599	0.0999	0	1
Rainfall rate	2,936	5.3339	1.6018	2.789	9.2575

Note. — Per capita income (PCI) and per capita consumption (PCE) figures are in monthly and in 2000 Indonesia rupiah. The values are transformed into logarithmic values. ADLs denote activities of daily living index. Log of household assets are calculated from total value of assets for each household in 2000 Indonesia rupiah.

Table 3: Full Risk Sharing: Individual and Community Level

	Log of per capita expenditure				
	(1)	(2)	(3)	(4)	(5)
Log of per capita income	0.170*** (0.006432)	0.116*** (0.0064)	0.055*** (0.0067)	0.0542*** (0.00784)	0.117** (0.0457)
Households	3914	3914	3914	3914	2983
Observations	9582	9582	9582	9582	8647
R^2	0.2163	0.095	0.239	0.7249	0.191
Wald $\chi^2(1)$	1793.32				
p-value	0.000				
F-stat		335.5	7.60		166.5
p-value		0.00	0.000		0.000
Kleibergen-Paap rk LM stat					58.516
Chi-sq(2) p-value					0.000
Cragg-Donald Wald F stat					36.017
Kleibergen-Paap rk Wald F stat					30.371
Hansen $J-$statistic					0.439
$\chi^2(1)$ p-value					0.507
Estimation method	RE (robust error)	FE (robust error)	FE (robust error)	OLS (clustered-robust error)	IV-2SLS (clustered-robust error)
Fixed effects	No FEs	HH FE only	All FEs	HH & wave only	All FEs

Note. — All variables are in 2000 Indonesian rupiah. RE means random effects, and FE means fixed effects. In Column (4), ADLs of the household's head, log of household assets, and rainfall rate are used as instruments. The number of clusters is 310 villages. Coefficients significant at the 10% level are denoted by * , at the 5% level by **, and at the 1% level by ***.

Table 4: Full risk sharing: checking endogeneity

	Log of per capita expenditure	
	(1)	(2)
ADLs	-0.0716	
	(0.331)	
Log of assets	0.230***	
	(0.0178)	
Rainfall rate	-0.0734***	
	(0.00957)	
Residuals		-0.136***
		(0.0278)
Log of per capita income		0.250***
		(0.0265)
Constant	7.723***	9.437***
	(0.425)	(0.294)
Households	3185	3185
Observations	8849	8849
R-sq within	0.038	0.102
F-stat	68.59	185.6
p-value	0.000	0.000
Estimation method	FE	FE

Note. — All variables are in 2000 Indonesian rupiah. This table provides instrument checks for full risk sharing tests in Table 3. Robust standard errors are reported in parentheses. Coefficients significant at the 10% level are denoted by * , at the 5% level by **, and at the 1% level by ***.

Table 5: Nested regressions

	Log of per capita expenditure	
	(1)	(2)
Log of previous per capita consumption	0.452***	0.152***
	(0.0275)	(0.0353)
Log of previous per capita consumption$\times\eta$	-0.0543*	-0.181***
	(0.0213)	(0.0337)
Log of previous per capita income	0.0285***	0.370***
	(0.00559)	(0.0432)
η	0.289***	0.265***
	(0.0282)	(0.0280)
Constant	4.255***	7.584***
	(0.248)	(0.495)
Observations	6232	5928
Households	3116	2964
Wald $\chi^2(4)$	1735.1	573.10
Prob > χ^2	0.0000	0.00
Sargan-Hansen statistic		0.056
$\chi^2(1)$ p-value		0.8129
Kleibergen-Paap rk LM statistic		125.083
$\chi^2(2)$ p-value		0.0000
Cragg-Donald Wald F statistic		72.06
Kleibergen-Paap rk Wald F statistic		63.445
Estimation method	OLS	IV-2SLS

Note. — All variables are in 2000 Indonesian rupiah. η is in log form. Instruments used in Column (2) are the log of asset of the previous wave and rainfall rate of the previous wave. Robust standard errors in parentheses for Column (1) and (2). Coefficients significant at the 10% level are denoted by * , at the 5% level by **, and at the 1% level by ***.

Table 6: Nested regressions: Agriculture

	Log of per capita expenditure	
	(1)	(2)
Log of previous per capita consumption	0.439***	0.105
	(0.0615)	(0.109)
Log of previous per capita consumption×η	-0.0756	-0.142*
	(0.0442)	(0.0655)
Log of previous per capita income	0.0210	0.405***
	(0.0119)	(0.111)
η	0.214***	0.175*
	(0.0507)	(0.0704)
Constant	6.031***	7.868***
	(0.643)	(1.035)
Observations	1072	1011
Households	544	537
Wald $\chi^2(4)$	177.63	93.83
Prob > χ^2	0.0000	0.00
Sargan-Hansen statistic		0.616
$\chi^2(2)$ p-value		0.4327
Kleibergen-Paap rk LM statistic		27.475
$\chi^2(2)$ p-value		0.0000
Cragg-Donald Wald F statistic		13.188
Kleibergen-Paap rk Wald F statistic		13.927
Estimation method	OLS	IV-2SLS

Note. — All variables are in 2000 Indonesian rupiah. η is in log form. Instruments used in Column (2) are the ADLs of the household's head from the previous wave, the log of asset of the previous wave and rainfall rate of the previous wave. Robust standard errors in parentheses for Column (1) and (2). Coefficients significant at the 10% level are denoted by * , at the 5% level by **, and at the 1% level by ***. from IFLS dataset.

Fig. 1.— The averages of community consumption and income.

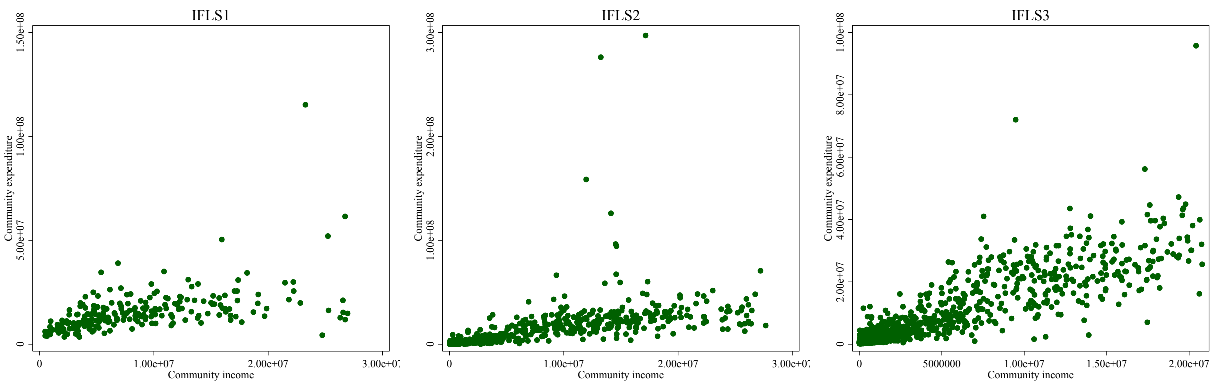

Table 7: Moral hazard only regressions

	Consumption moment					
	(1)	(2)	(3)	(4)	(5)	(6)
γ value	1.00	1.20	1.40	1.60	1.80	2.00
Log of previous	-0.618***	-0.646***	-0.663***	-0.671***	-0.674***	-0.675***
consumption moment	(0.0771)	(0.0742)	(0.0721)	(0.0706)	(0.0694)	(0.0686)
Average log of	0.214***	0.270***	0.325***	0.378***	0.431***	0.482***
previous income	(0.0592)	(0.0732)	(0.0882)	(0.104)	(0.121)	(0.137)
Observations	620	620	620	620	620	620
Community	310	310	310	310	310	310
R-square	0.473	0.502	0.515	0.518	0.515	0.509
adj. R-square	-0.060	-0.002	0.024	0.029	0.023	0.012
$F-$statistics	55.11	61.78	66.16	68.55	69.58	69.80
$p-$value	0.000	0.000	0.000	0.000	0.000	0.000
Kleibergen-Paap rk LM statistic	36.478	40.417	43.87	46.698	48.934	50.673
$\chi^2(3)$ $p-$value	0.000	0.000	0.000	0.000	0.000	0.000
Cragg-Donald Wald F stat.	17.134	18.893	20.329	21.471	22.375	23.093
Kleibergen-Paap rk Wald F stat.	10.436	11.529	12.467	13.230	13.836	14.316
Hansen J statistic	0.556	0.570	0.573	0.572	0.569	0.566
$\chi^2(2)$ $p-$value	0.757	0.752	0.7507	0.7512	0.7522	0.7533

Note. — This table presents moral hazard tests using raw moment simulations based on (7). All variables are in 2000 Indonesian rupiah. Instruments used in this estimation are average of household asset in a community, average of ADLs, and rainfall. Robust IV-2SLS estimations with fixed-effects are employed. Standard errors are reported in parentheses. Coefficients significant at the 10% level are denoted by * , at the 5% level by **, and at the 1% level by ***.

Table 8: Limited commitment only regression

	Consumption ratio: Wave 3		
	(1)	(2)	(3)
Consumption ratio: Wave 2	0.0396	0.505*	0.527*
	(0.0234)	(0.214)	(0.249)
Join Rosca =1	0.352***	0.253**	0.478
	(0.0859)	(0.0911)	(0.275)
Agriculture = 1	-0.106**	0.00661	0.00572
	(0.0383)	(0.0463)	(0.0468)
Join Rosca × consumption ratio (Wave 2)			-0.184
			(0.273)
Constant	1.020***	0.442*	0.418
	(0.0374)	(0.208)	(0.244)
Households	2999	2745	2745
R^2	0.031		
$F-$statistics	8.79		
$p-$value	0.0000		
Wald $\chi^2(4)$		31.42	33.51
$p-$value		0.0000	0.0000
Wu-Hausman		75.6824	68.442
$p-$value		0.0000	0.0000
Sargan $\chi^2(2)$		0.4832	0.4298
$p-$value		0.7854	0.8066
Estimation method	OLS	IV-2SLS	IV-2SLS
	Robust	Cluster robust	Cluster robust

Note. — All variables are in 2000 Indonesian rupiah. Robust standard errors in parentheses. The instruments are log of asset, ADLs and rainfall rate in the previous wave. Coefficients significant at the 10% level are denoted by * , at the 5% level by **, and at the 1% level by ***.